

Introduction

Spaceborne Global Navigation Satellite System Reflectometry (GNSS-R) has emerged as a new technique for ocean wind speed retrieval, offering unprecedented revisit frequency and all-weather capacity. However, the track-wise sampling of current GNSS-R missions leads to **substantial spatial and temporal gaps**. Fig.1 presents the spatial coverage of Cyclone GNSS (CYGNSS) Level 2 products after 6-hour rescaling, with an averaged coverage rate of about 30%. The gaps even further increase with a higher temporal resolution. These gaps hinder further applications of GNSS-R ocean wind speed products.

Thus, this study explores to **use a physics-informed 4DVarNet** to reconstruct **gap-free GNSS-R ocean wind field with up to hourly temporal resolution** through learning spatiotemporal evolution patterns.

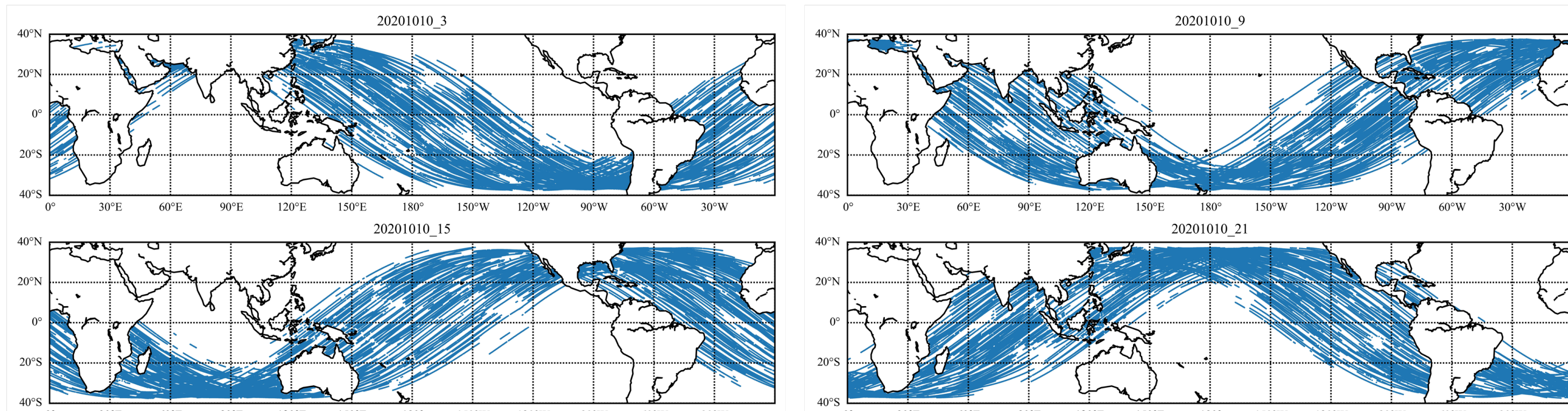


Fig. 1: Tracks of 8-satellite CYGNSS Level 2 ocean wind products with 6-hour temporal and $0.25^\circ \times 0.25^\circ$ spatial resolutions on October 10, 2020.

4DVarNet Scheme

Based on the principle of 4D variational (4DVar) data assimilation, Ronan et al. [1] proposed a **neural implementation** as shown in Fig. 2, consisting of two main components: **one-step predication model Φ** , and **gradient solver**. The gappy GNSS-R wind maps will be input as the initial state estimation into the gradient solver to compute the 4DVar cost U_Φ . Automatic differentiation against the state x^k can be computed and update the state estimation x^{k+1} . This process is implemented by a 2D convolutional LSTM. A supervised learning strategy is applied with a weighted loss of errors of reconstructed wind speeds and **wind gradients**.

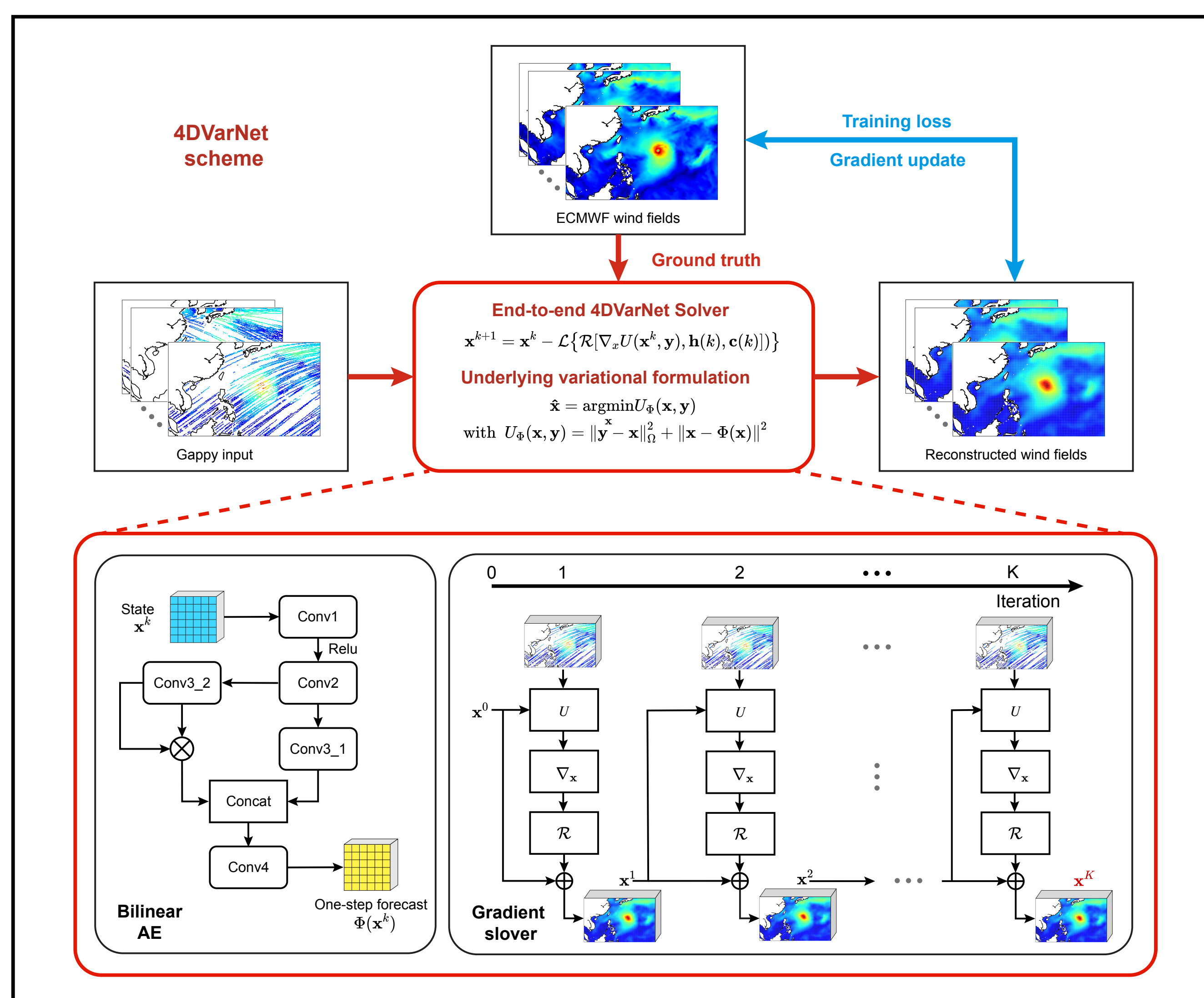


Fig. 2: 4DVarNet scheme for GNSS-R ocean wind field reconstruction. The neural scheme then minimizes the 4D variational cost function. Gap-free ECMWF winds serve as the ground truth.

Reference

- [1] Fablet et al., 2021. Learning variational data assimilation models and solvers, *JAMES*, 10.1029/2021MS002572.
 [2] Du et al., 2026. Gap-free GNSS-R wind field reconstruction: A neural mapping scheme and initial validation, *RSE*, 10.1016/j.rse.2025.115218.

Results and Discussions

Reconstructed wind fields

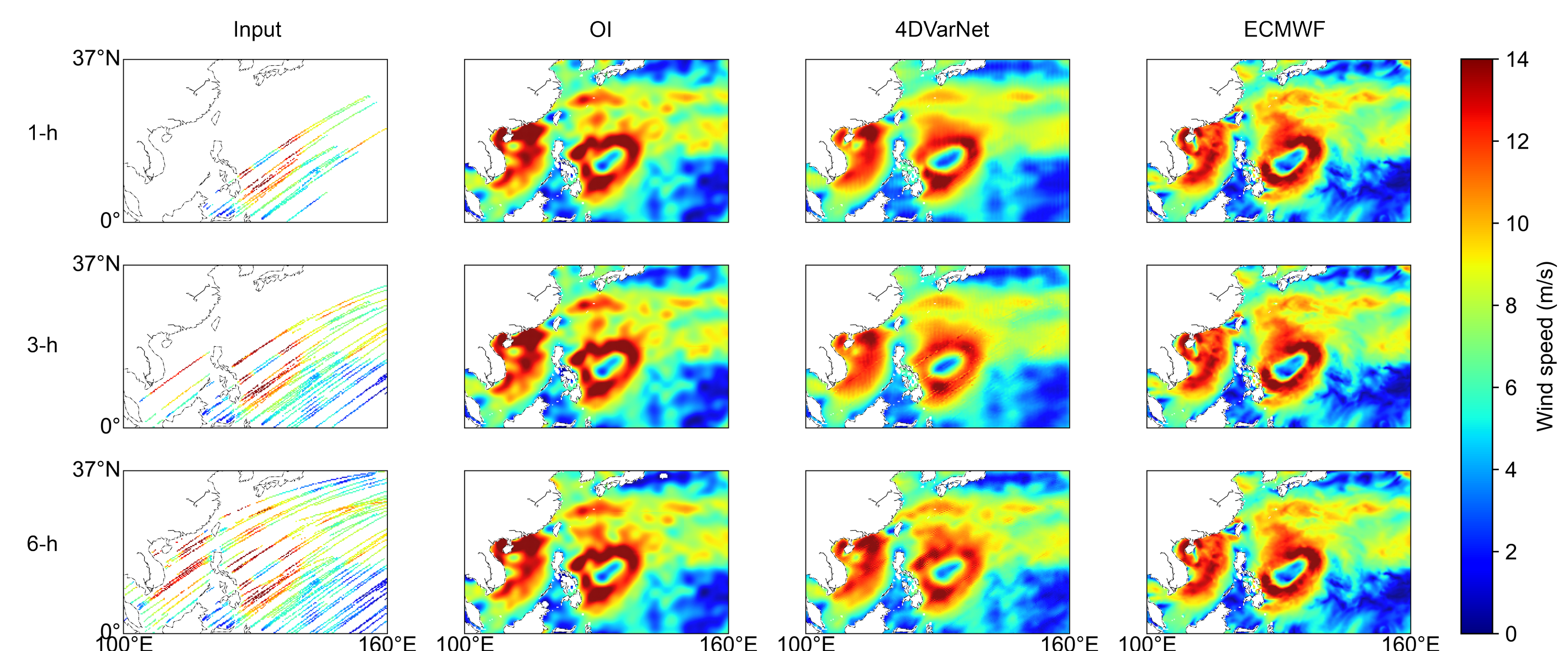


Fig. 3: One sample of 1-hour, 3-hour, and 6-hour reconstructed wind fields by optimal interpolation (OI) and 4DVarNet. The RMSEs of three 4DVarNet winds compared to ECMWF ERA5 wind products are about 1.40 m/s, 1.41 m/s, and 1.48 m/s, respectively.

Peak detection in Super Typhoon Surigae

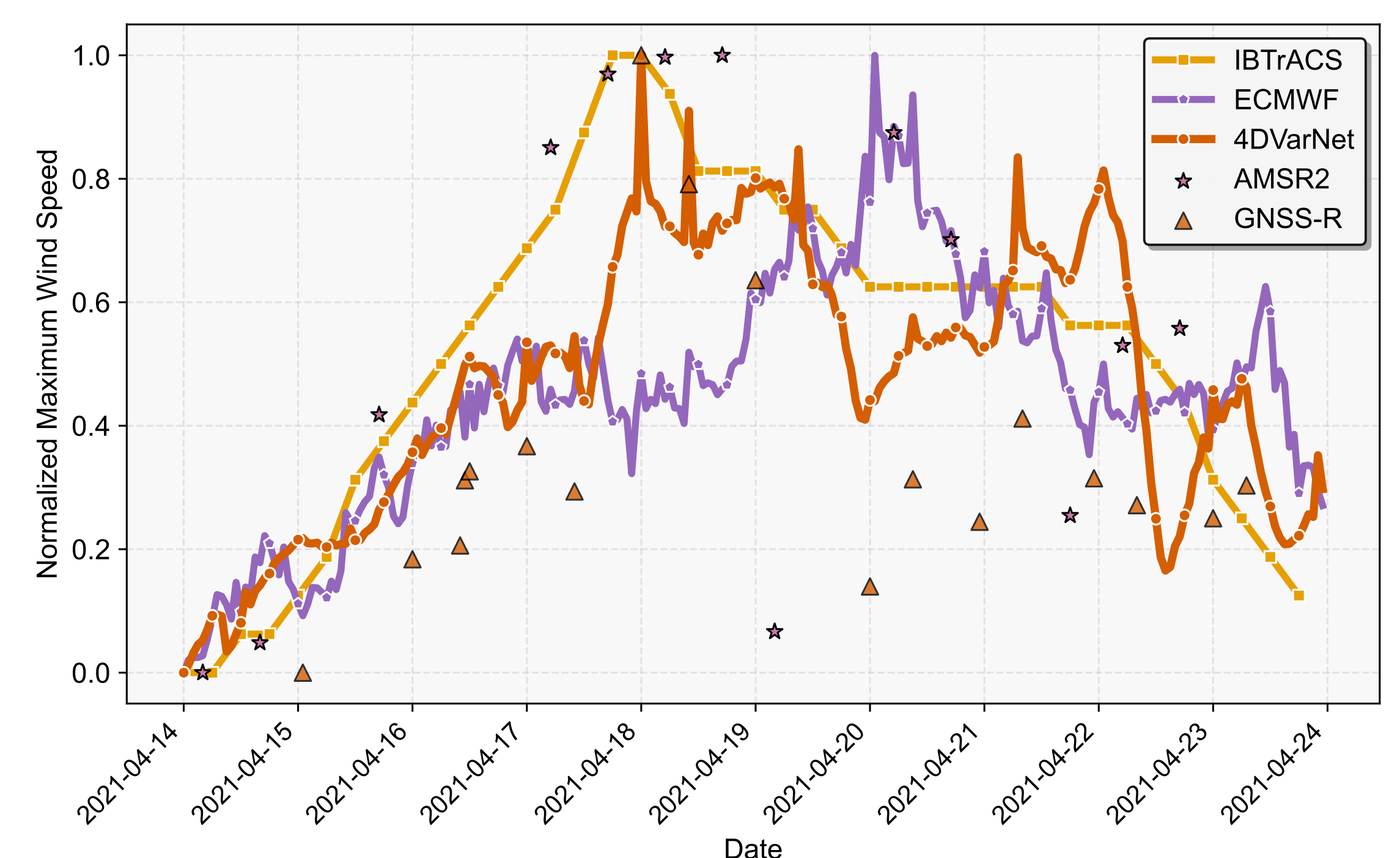


Fig. 4: The time series of normalized maximum wind speeds from input GNSS-R, 4DVarNet, ECMWF, AMSR2, and IBTrACS winds. The 4DVarNet wind reached its peak intensity of approximately 32 m/s on April 18, 2021.

Asymmetrical structure in Tropical Storm Kompas

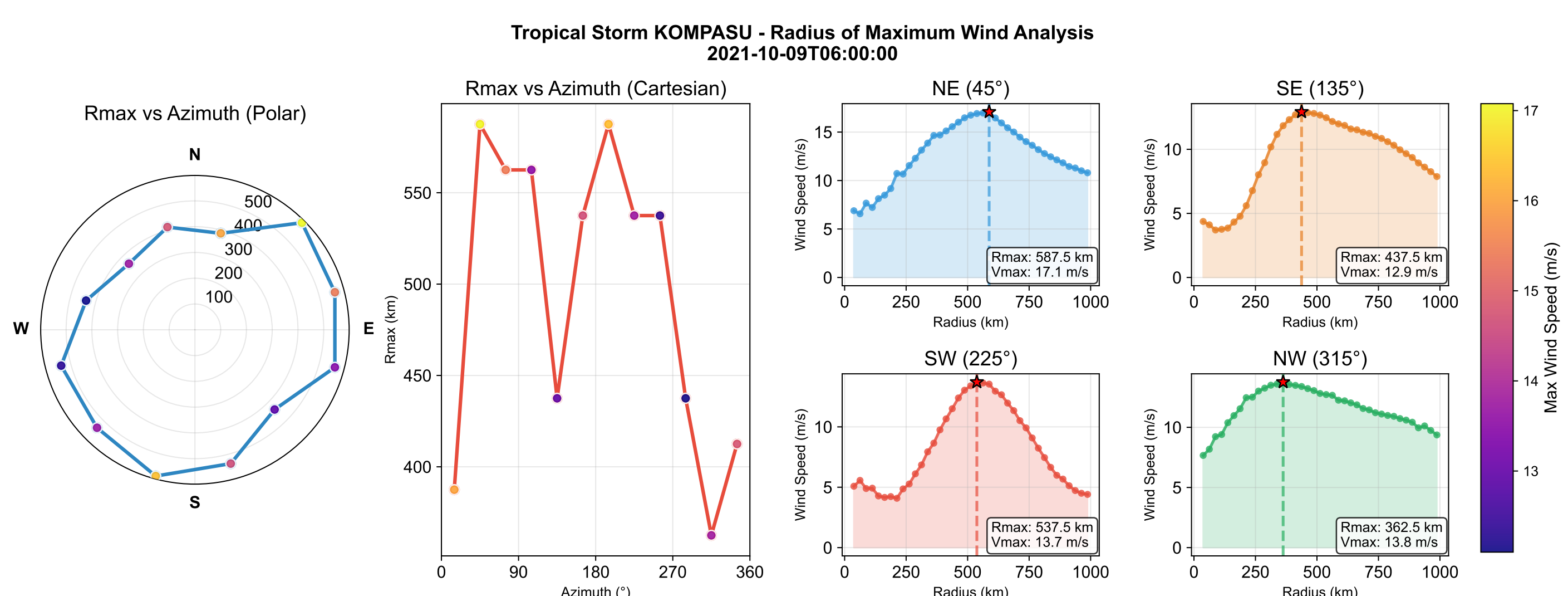


Fig. 5: Radius and azimuth analysis of maximum 4DVarNet winds on 2021-10-09T06:00:00. Among the four quadrants, V_{max} and R_{max} are detected in the NE quadrant with 17 m/s and 587.5 km. R_{max} is 362.5 km in the NW quadrant, 38% shorter than the NE R_{max} .

Conclusions

In this study, we apply a physics-informed 4DVarNet scheme to reconstruct gap-free GNSS-R ocean surface wind fields, exhibiting **great performance with multiple wind references**. Moreover, case studies demonstrate the capability of the reconstructed fields to **capture the coverage, evolution, and asymmetrical characteristics of tropical cyclones**. More details can be found in our paper [2].

Acknowledgment

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